Generative Adversarial Networks

Deep Learning (DSE316/616)

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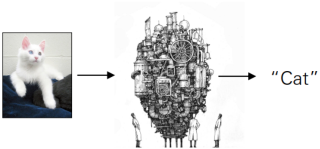
Disclaimer

- Much of the material and slides for this lecture were borrowed from
    - Bernhard Schölkopf's MLSS 2017 lecture,
    - Tommi Jaakkola's 6.867 class,
    - CMP784: Deep Learning Fall 2021 Erkut Erdem Hacettepe University
    - Fei-Fei Li, Andrej Karpathy and Justin Johnson's CS231n class
    - Hongsheng Li's ELEG5491 class
    - Tsz-Chiu Au slides
    - Mitesh Khapra Class notes

Discriminative vs. Generative Models

$$p(y|x)$$

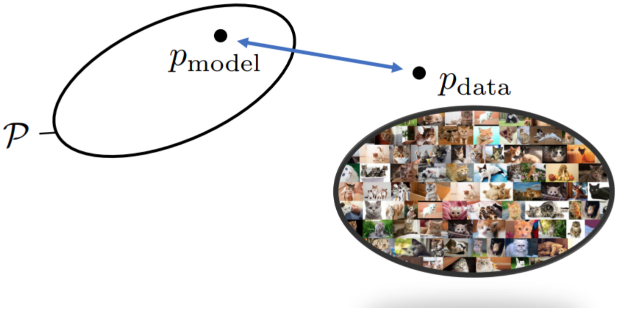


Discriminative models

$$p(x|y)$$

Generative models

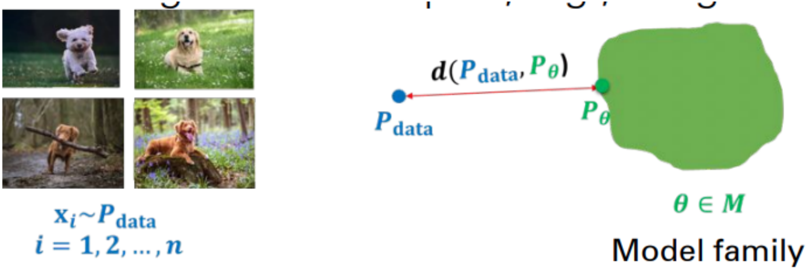
Generative Modeling



- **Goal:** Learn some underlying hidden structure of the training samples to generate novel samples from same data distribution

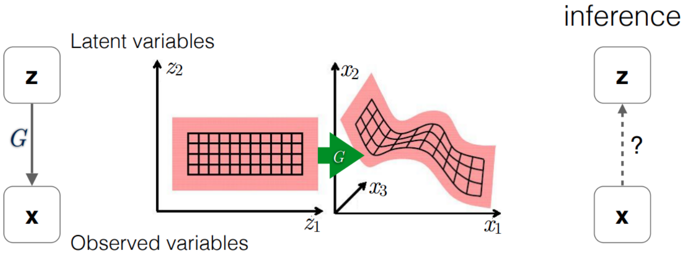
Learning a generative model

- We are given a training set of examples, e.g., images of dogs

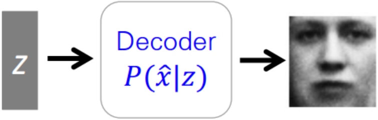


- We want to learn a probability distribution $p(x)$ over images x s.t.
  - **Generation:** If we sample x_{new} $p(x)$, x_{new} should look like a dog (sampling)
  - **Density estimation:** $p(x)$ should be high if x looks like a dog, and low otherwise (anomaly detection)
  - **Unsupervised representation learning:** We should be able to learn what these images have in common, e.g., ears, tail, etc. (features)

Latent variable model

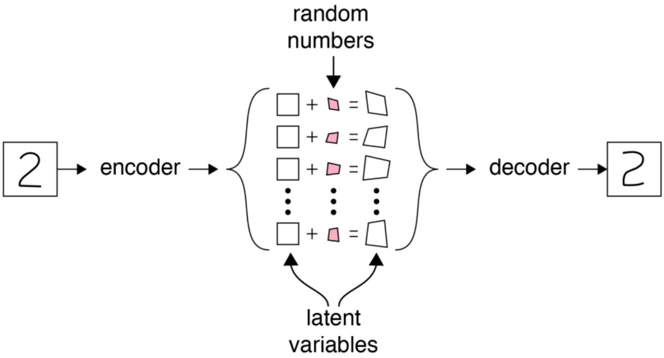


Sample from g(z)
e.g. Standard
Gaussian

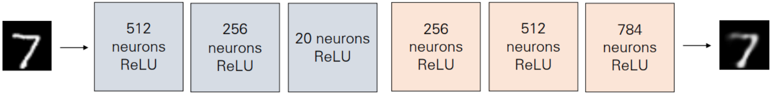


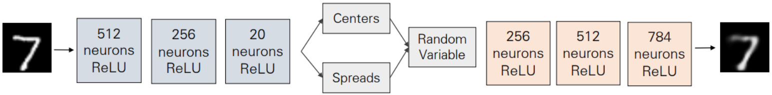
$\boxed{z \sim g(z)}$ $\boxed{\hat{x} = f(z)}$ $\boxed{\hat{x} \sim P(x|z)}$

Variational Autoencoders



Variational Autoencoders





Variational AE

$$
\begin{aligned}
\log p_\theta(x^{(i)}) &= \mathbf{E}_{z\sim q_\phi(z|x^{(i)})}\left[\log p_\theta(x^{(i)})\right] \quad (p_\theta(x^{(i)}) \text{ Does not depend on } z) \\
&= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})}\right] \quad (\text{Bayes' Rule}) \\
&= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})} \frac{q_\phi(z \mid x^{(i)})}{q_\phi(z \mid x^{(i)})}\right] \quad (\text{Multiply by constant}) \\
&= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z)}\right] + \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z \mid x^{(i)})}\right] \quad (\text{Logarithms}) \\
&= \underbrace{\mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z))}_{\mathcal{L}(x^{(i)},\theta,\phi)\ \text{"Elbow"}} + \underbrace{D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z \mid x^{(i)}))}_{\geq 0}
\end{aligned}
$$

$$\log p_\theta(x^{(i)}) \geq \mathcal{L}(x^{(i)}, \theta, \phi)$$

Variational lower bound (elbow)

$$\theta^*, \phi^* = \arg\max_{\theta,\phi} \sum_{i=1}^{N} \mathcal{L}(x^{(i)}, \theta, \phi)$$

Training: Maximize lower bound

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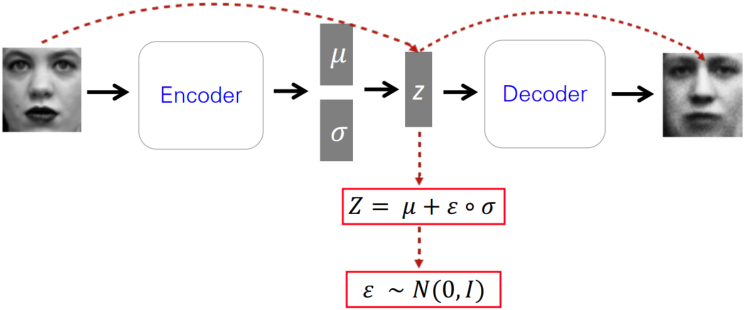
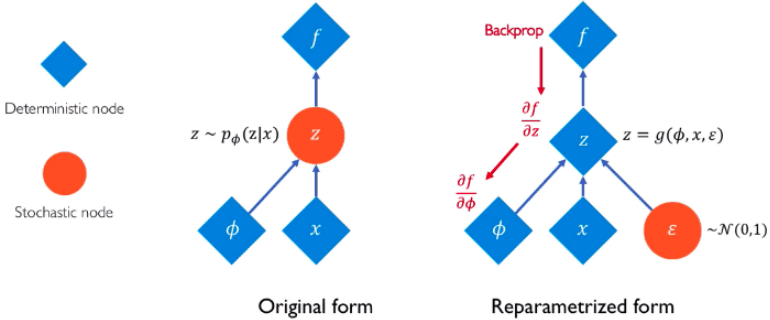
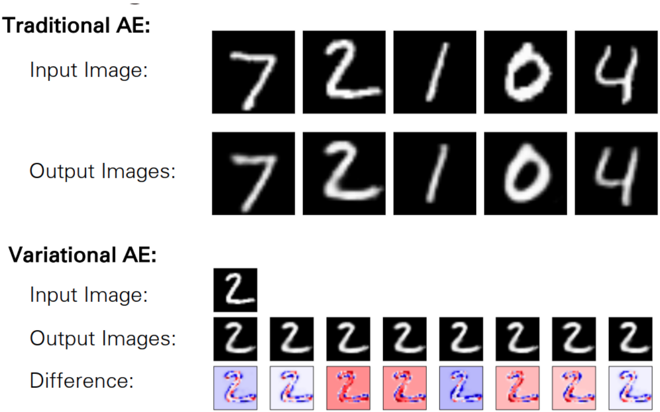
Reparametrization Trick



Reparametrization Trick



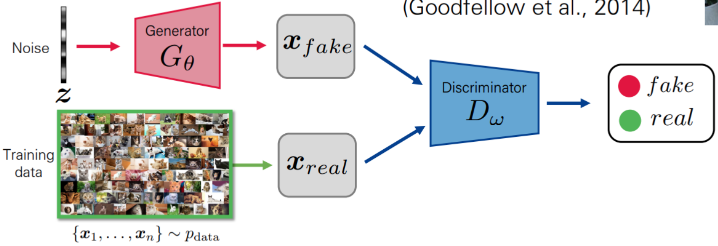
Training VAE



Genetive Adversarial Networks (GANs)

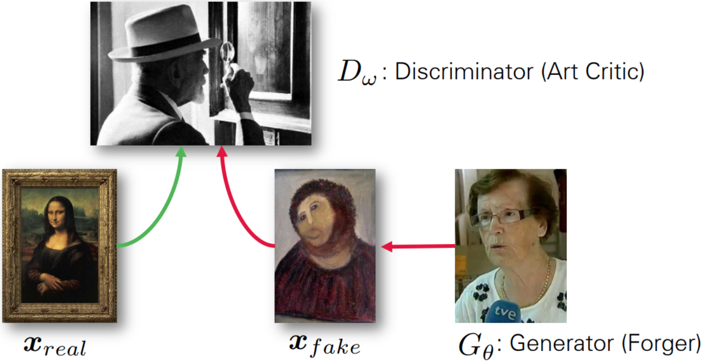
Genetive Adversarial Networks (GANs)

(Goodfellow et al., 2014)



- A game between a generator $G_\theta(z)$ and a discriminator $D_\omega(x)$
  - Generator tries to fool discriminator (i.e. generate realistic samples)
  - Discriminator tries to distinguish fake from real samples

Intuition behind GANs



GAN Training: Minimax Game

$$\min_{\theta} \max_{\omega} \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}} [\log D_{\omega}(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}} [\log (1 - D_{\omega}(G_{\theta}(\boldsymbol{z})))]$$

Real data

Noise vector used to generate data

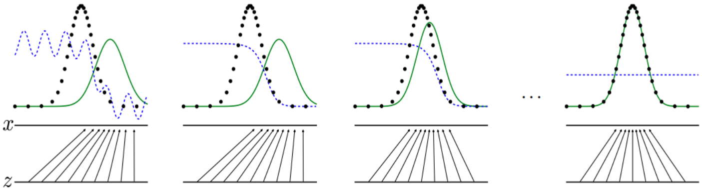
$$J^{(D)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}} \log D(\boldsymbol{x}) - \frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log (1 - D(G(\boldsymbol{z})))$$

Cross-entropy loss for binary classification

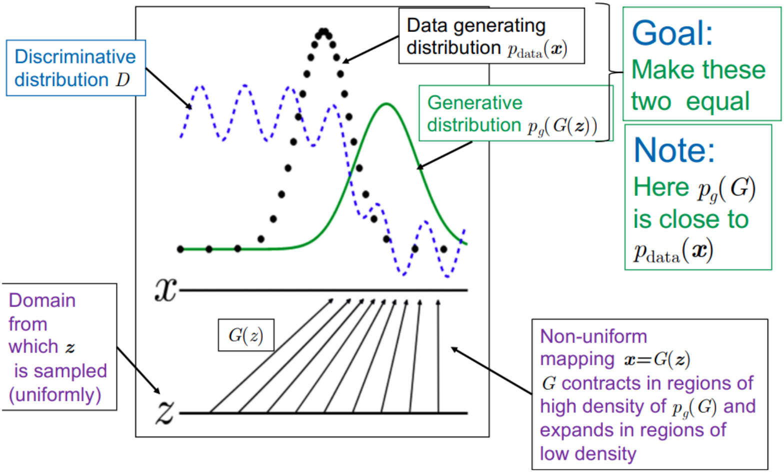
$$J^{(G)} = -\frac{1}{2}\mathbb{E}_{\boldsymbol{z}} \log D(G(\boldsymbol{z}))$$

Generator maximizes the log-probability of the discriminator being mistaken

Training Procedure

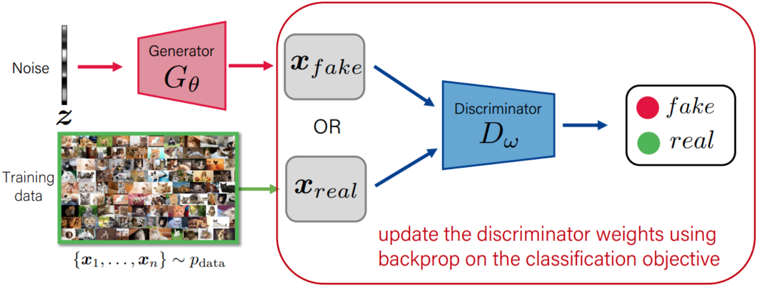


Training Procedure



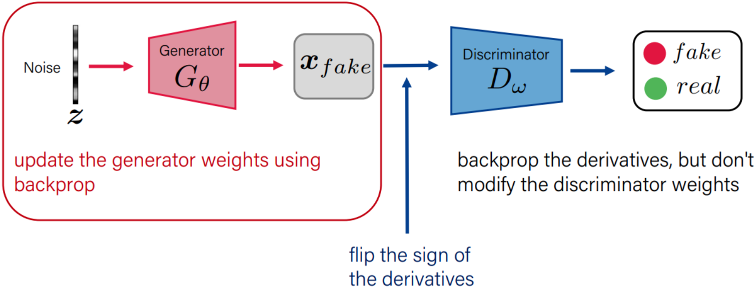
Training Procedure

- Updating the discriminator:



Training Procedure

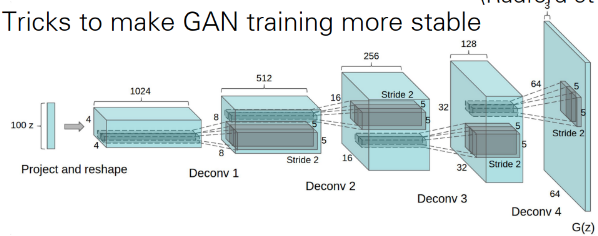
- Updating the generator:



Deep Convolutional GANs (DCGAN)

(Radford et al., 2015)

- **Idea:** Tricks to make GAN training more stable



- No fully connected layers
- Batch Normalization (Ioffe and Szegedy, 2015)
- Leaky Rectifier in D
- Use Adam (Kingma and Ba, 2015)
- Tweak Adam hyperparameters a bit (lr=0.0002, b1=0.5)

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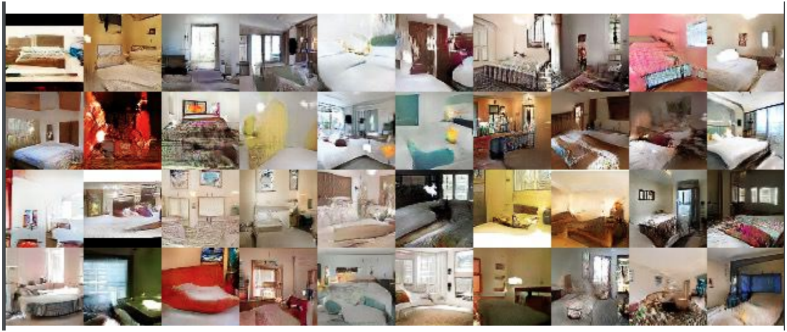
Deep Convolutional GANs (DCGAN)

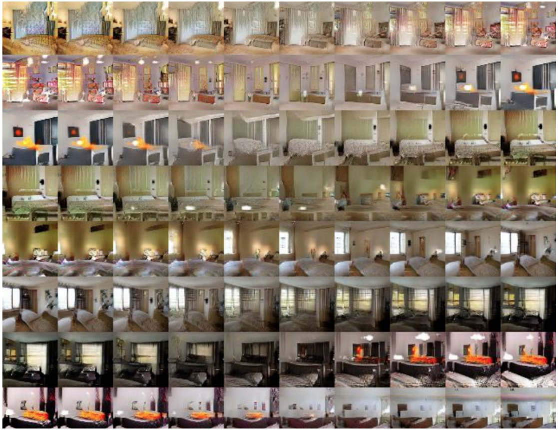


Deep Convolutional GANs (DCGAN)

Walking over the latent space

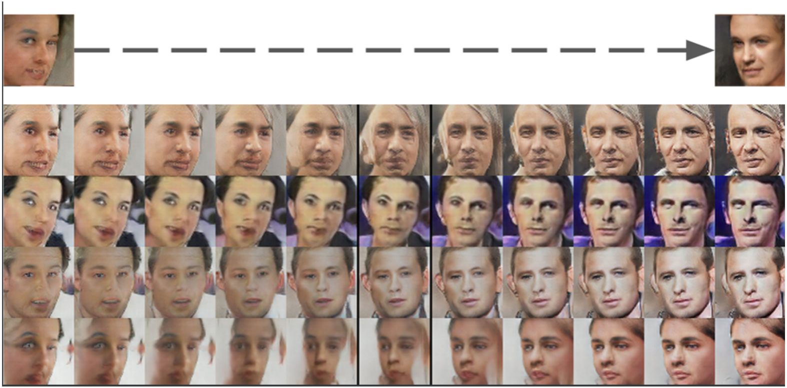
(Radford et al., 2015)

- Interpolation suggests non-overfitting behavior



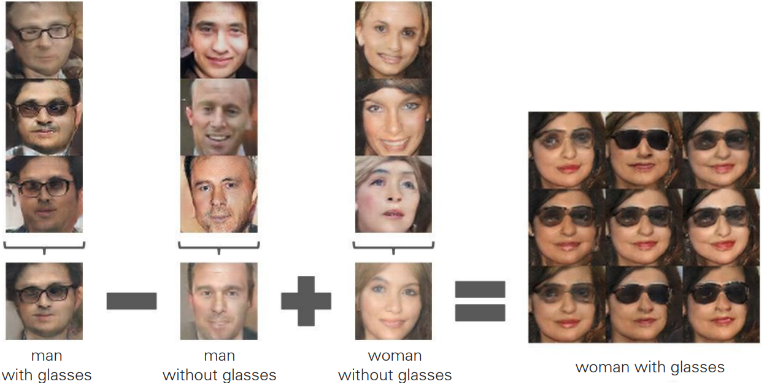
Deep Convolutional GANs (DCGAN)

- Walking over the latent space



Deep Convolutional GANs (DCGAN)

- Vector Space Arithmetic



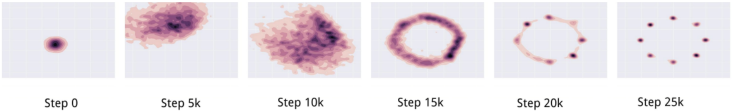
GAN Failures: Mode Collapse

$$\min_G \max_D V(G, D) \neq \max_D \min_G V(G, D)$$

- **D** in inner loop: convergence to correct distribution
- **G** in inner loop: place all mass on most likely point

Mode Collapse: Solutions

- **Unrolled GANs** (Metz et al 2016): Prevents mode collapse by backproping through a set of (k) updates of the discriminator to update generator parameters

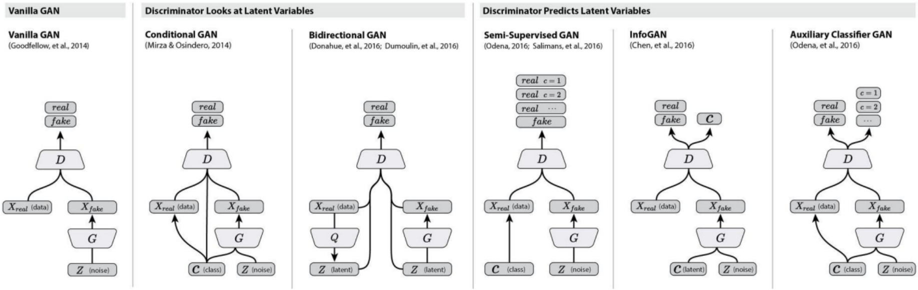


- **VEEGAN** (Srivastava et al 2017): Introduce a reconstructor network which is learned both to map the true data distribution p(x) to a Gaussian and to approximately invert the generator network.

GAN Evaluation

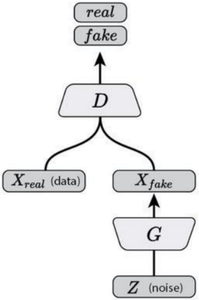
- Quantitatively evaluating GANs is not straight forward:
  - Max Likelihood is a poor indication of sample quality
- Some evaluation metrics
  - Inception Score (IS):
    - y = labels given gen. image. p(y|x) is from classifier - InceptionNet
    - $IS(p_g) = e^{E_{x \in P_g} KL(P_m(y|x)||p(y))}$
  - Fréchet inception distance (FID): (Currently most popular)
    - Estimate mean m and covariance C from classifier output - InceptionNet
    - $$d^2((\boldsymbol{m}, \boldsymbol{C}), (\boldsymbol{m}_w, \boldsymbol{C}_w)) = \|\boldsymbol{m} - \boldsymbol{m}_w\|_2^2 + \mathrm{Tr}\left(\boldsymbol{C} + \boldsymbol{C}_w - 2\left(\boldsymbol{C}\boldsymbol{C}_w\right)^{1/2}\right)$$
  - Kernel MMD (Maximum Mean Discrepancy):
    - $$\mathrm{MMD}(\mathbb{P}_r, \mathbb{P}_g) = \left(\mathbb{E}_{\substack{\mathbf{x}_r, \mathbf{x}_r' \sim \mathbb{P}_r, \\ \mathbf{x}_g, \mathbf{x}_g' \sim \mathbb{P}_g}}\left[k(\mathbf{x}_r, \mathbf{x}_r') - 2k(\mathbf{x}_r, \mathbf{x}_g) + k(\mathbf{x}_g, \mathbf{x}_g')\right]\right)^{\frac{1}{2}}$$

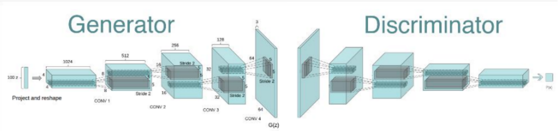
Subclasses of GANs



Vanilla GAN (Goodfellow et al., 2014

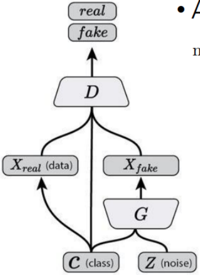
- Updating the generator:





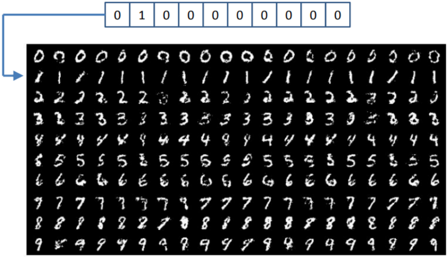
DCGAN (Radford et al., 2015)

Conditional GAN (Mirza et al)



- Add conditional variables $\boldsymbol{y}$ into G and D

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x}|\boldsymbol{y})] + \mathbb{E}_{\boldsymbol{z}\sim p_z(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z}|\boldsymbol{y})))]$$



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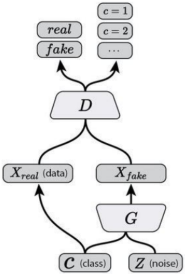
Auxiliary Classifier GAN(Odena et al)



- Every generated sample has a corresponding class label

$$L_S = E[\log P(S = real \mid X_{real})] + E[\log P(S = fake \mid X_{fake})]$$
$$L_C = E[\log P(C = c \mid X_{real})] + E[\log P(C = c \mid X_{fake})]$$

- D is trained to maximize $L_S + L_C$
- G is trained to maximize $L_C - L_S$

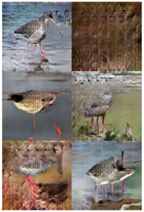
- Learns a representation for z that is independent of class label

Auxiliary Classifier GAN

monarch butterfly

goldfinch

daisy



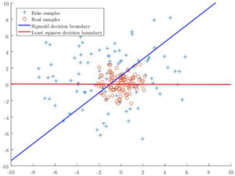
redshank

grey whale

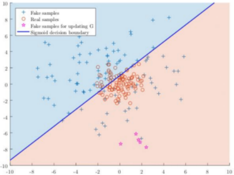
Least Squares GAN (LSGAN)

- Use a loss function that provides smooth and non-saturating gradient in discriminator D

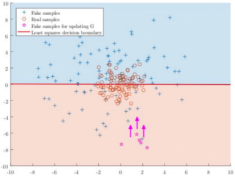
$$\min_D V_{\text{LSGAN}}(D) = \frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}\left[(D(\boldsymbol{x}) - b)^2\right] + \frac{1}{2}\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}\left[(D(G(\boldsymbol{z})) - a)^2\right]$$
$$\min_G V_{\text{LSGAN}}(G) = \frac{1}{2}\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}\left[(D(G(\boldsymbol{z})) - c)^2\right],$$



Decision boundaries of Sigmoid & Least Squares loss functions



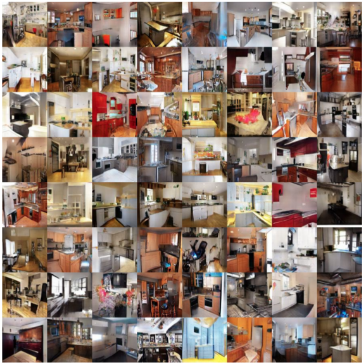
Sigmoid decision boundary



Least Squares decision boundary

Least Squares GAN (LSGAN)

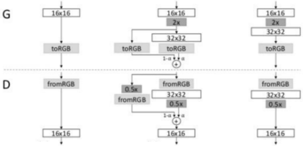
Church

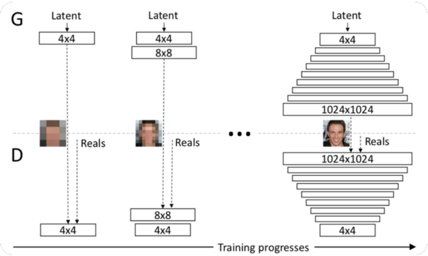


Kitchen

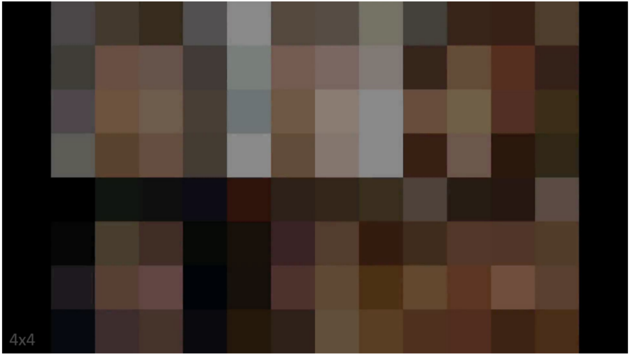
Progressive GANs(Karras et al., 2018)

- Progressively generate high-res images
- Multi-step training from low to high resolutions





Progressive GANs(Karras et al., 2018)



- Training process

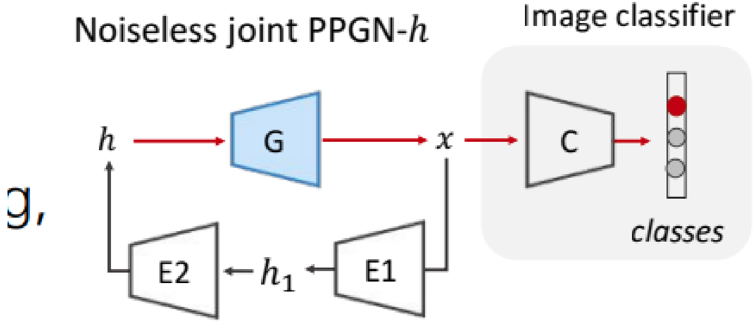
Progressive GANs(Karras et al., 2018)

GANs

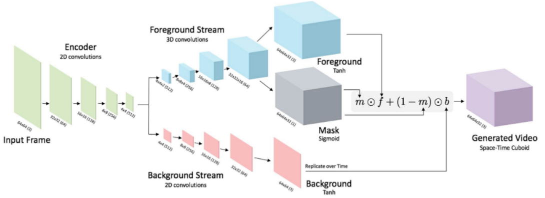
Next Class

Class-specific Image Generation (Nguyen et al., 2016)

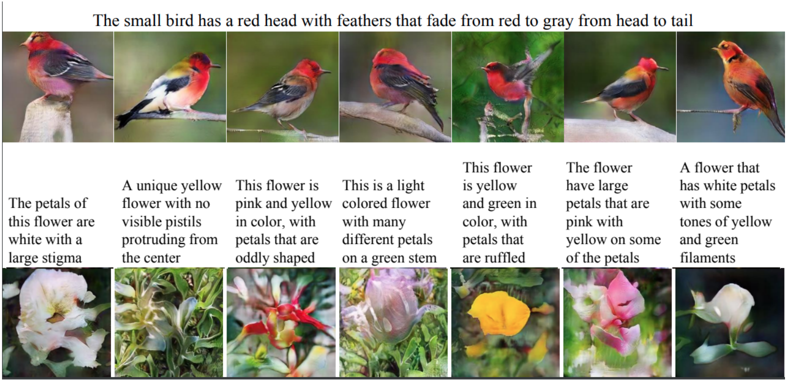
- Generates 227x227 realistic images from all ImageNet classes
- Combines adversarial training, moment matching, denoising autoencoders, and Langevin sampling



Video Generation (Vondrick et al., 2016)



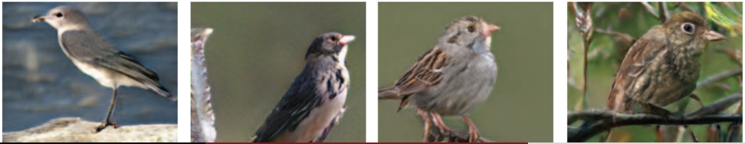
Text-to-Image Synthesis (Zhang et al., 2016)



Text-to-Image Synthesis (Zhu et al., 2019)

This bird has a white throat and a dark yellow bill and grey wings.	This particular bird has a belly that is yellow and brown.	This bird is a lime green with greyish wings and long legs.	This yellow bird has a thin beak and jet black eyes and thin feet.

This bird has wings that are grey and has a white belly.	This bird has wings that are black and has a white belly.	This is a grey bird with a brown wing and a small orange beak.	This bird has a short brown bill, a white eyering, and a medium brown crown.



Single Image Super-Resolution ((Ledig et al., 2016))

- Combine content loss with adversarial loss

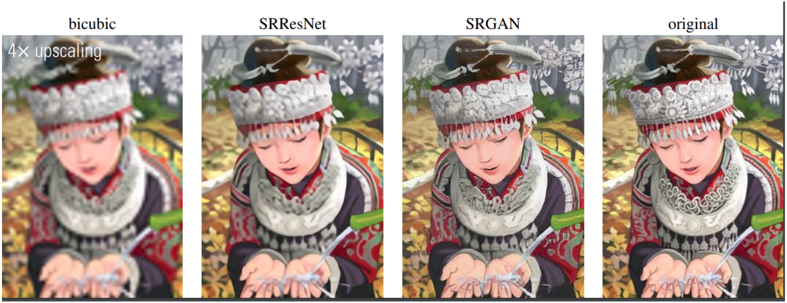


Image Inpainting (Pathak et al., 2016)

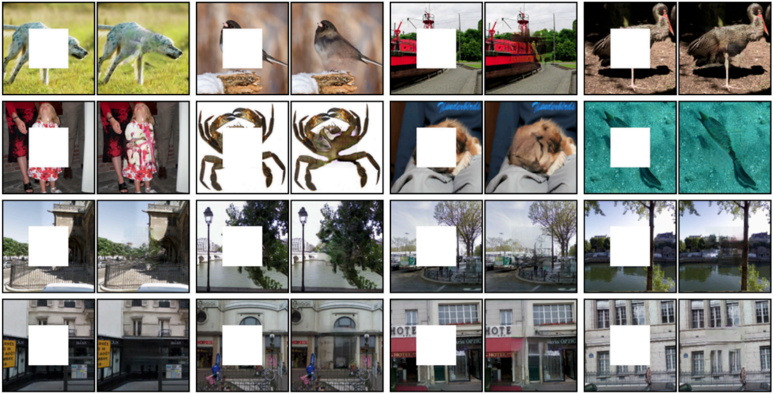


Image to Image Translation (Pix2Pix)

(Isola et al. 2016)

Image to Image Translation (Pix2Pix)

(Isola et al. 2016)

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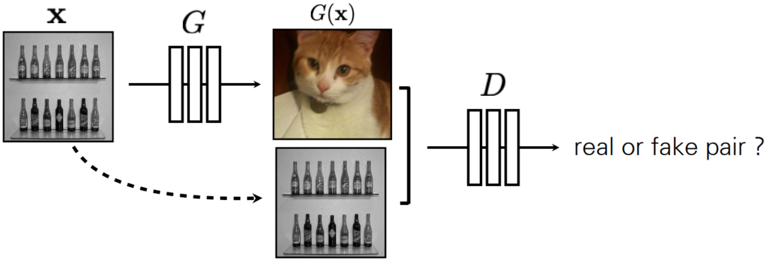
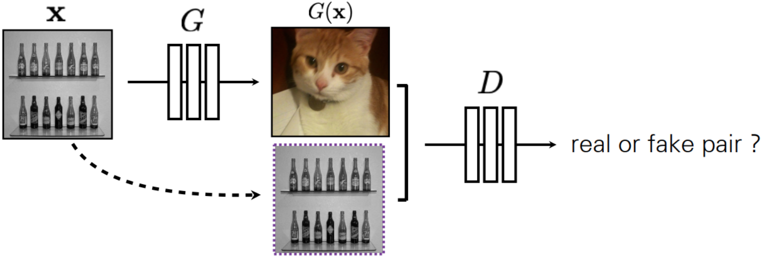


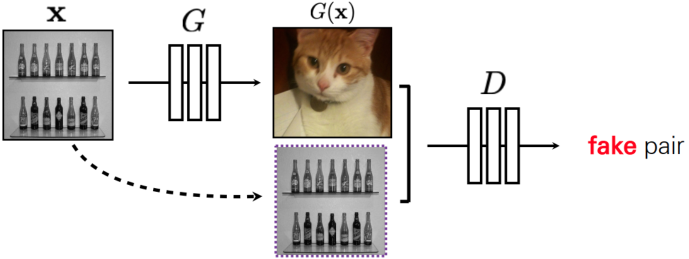
$$\arg\min_{G}\max_{D}\ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\ \log D(G(\mathbf{x})) \ + \ \log(1 - D(\mathbf{y}))\ ]$$

Image to Image Translation (Pix2Pix)



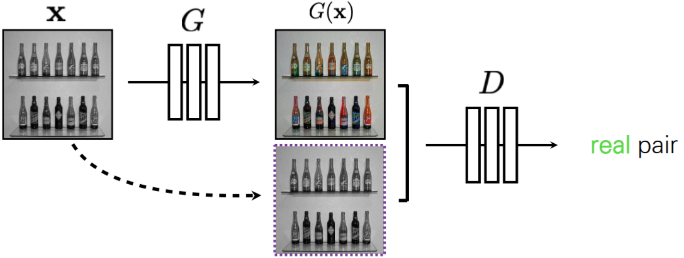
$$\arg\min_{G}\max_{D}\ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\ \log D(\boxed{\mathbf{x}}, G(\mathbf{x})) + \log(1 - D(\boxed{\mathbf{x}}, \mathbf{y}))\ ]$$

Image to Image Translation (Pix2Pix)



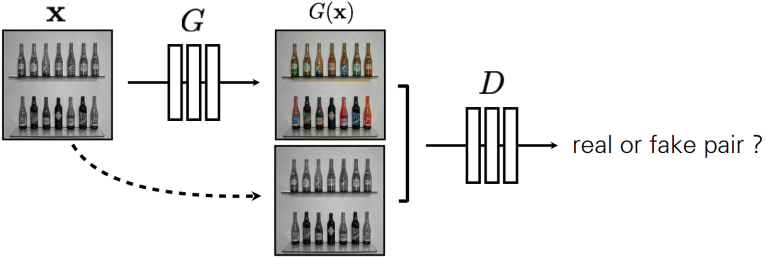
$$\arg\min_G \max_D \ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\ \log D(\boxed{\mathbf{x}}, G(\mathbf{x})) + \log(1 - D(\boxed{\mathbf{x}}, \mathbf{y}))\ ]$$

Image to Image Translation (Pix2Pix)



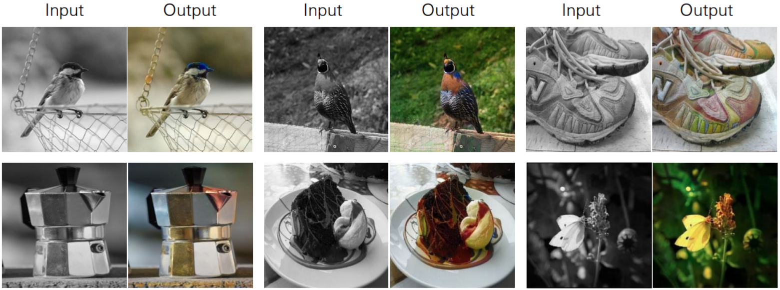
$$\arg\min_{G}\max_{D}\ \mathbb{E}_{\mathbf{x},\mathbf{y}}\left[\ \log D(\boxed{\mathbf{x}}, G(\mathbf{x})) + \log(1 - D(\boxed{\mathbf{x}}, \mathbf{y}))\ \right]$$

Image to Image Translation (Pix2Pix)

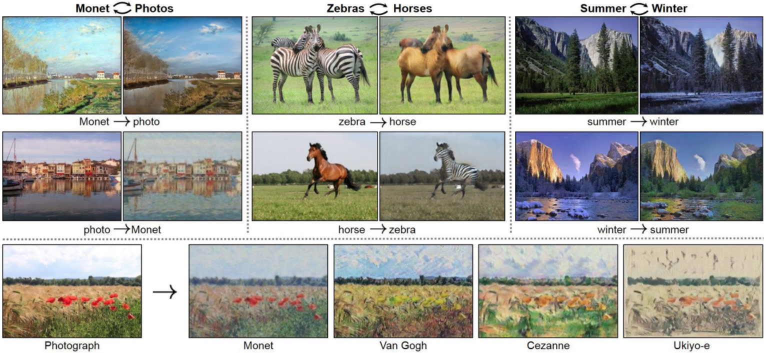


$$\boxed{\arg\min_G \max_D \ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\ \log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x},\mathbf{y}))\ ]}$$

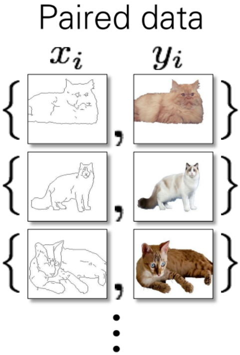
BW –> Color

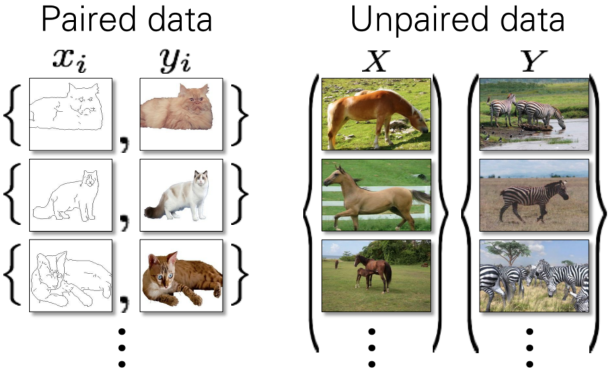


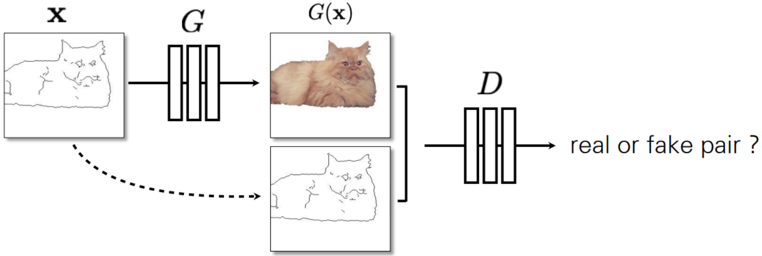
CycleGAN: Pix2Pix w/o input-output pairs



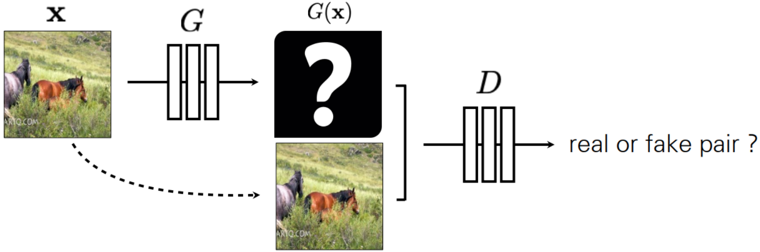
(Zhu et al. 2017)


Paired data
x_i
y_i


Paired data
x_i
y_i
Unpaired data
X
Y

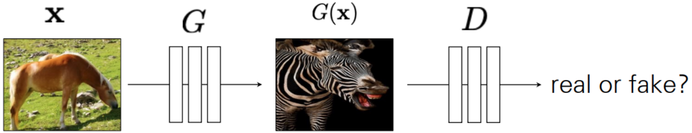


$$\arg\min_G \max_D \ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\ \log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x}, \mathbf{y}))\ ]$$



$$\arg\min_G \max_D \ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\ \log D(\mathbf{x}, G(\mathbf{x})) + \log(1 - D(\mathbf{x}, \mathbf{y}))\ ]$$

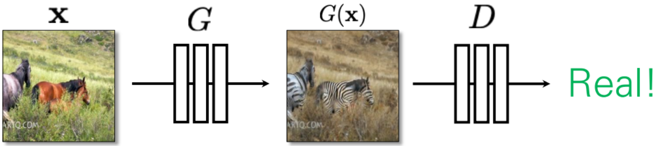
No input-output pairs!

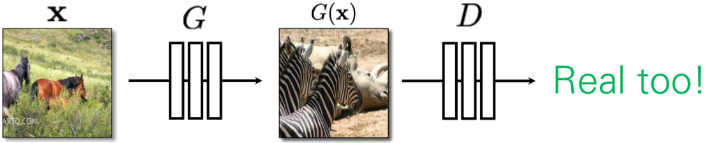


$$\arg\min_{G}\max_{D}\ \mathbb{E}_{\mathbf{x},\mathbf{y}}[\ \log D(G(\mathbf{x}))\ \ +\ \ \log(1 - D(\mathbf{y}))\ ]$$

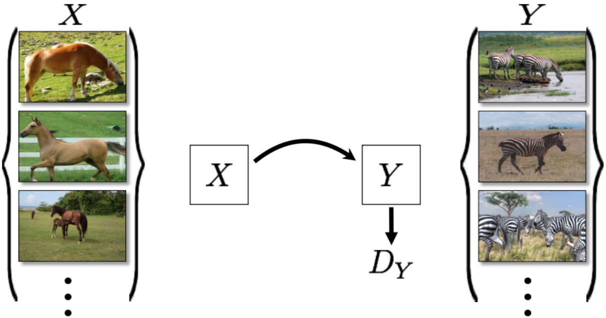
Usually loss functions check if output matches a target instance

GAN loss checks if output is part of an admissible set

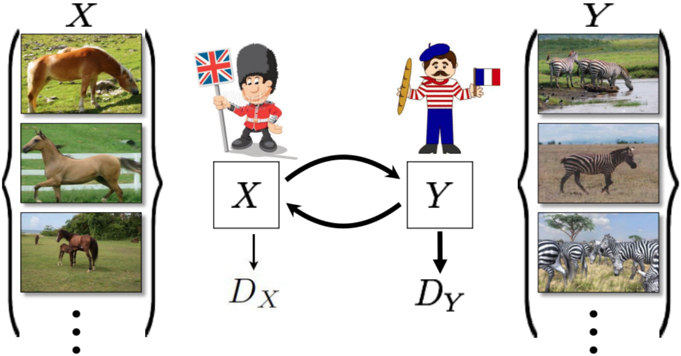

$\mathbf{x}$
G
$G(\mathbf{x})$
D
Real!



Nothing to force output to correspond to input

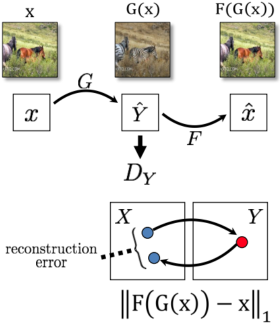


[Zhu et al. 2017], [Yi et al. 2017], [Kim et al. 2017]

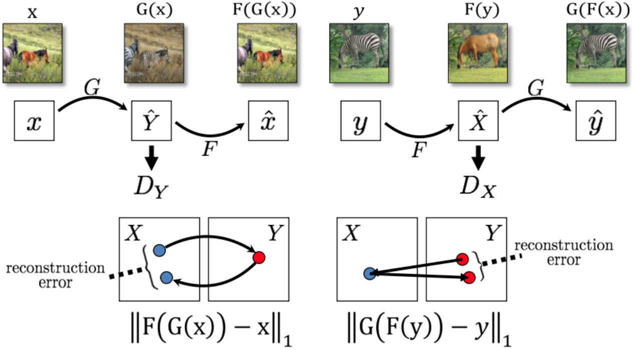


X
Y
X
Y
D_X
D_Y

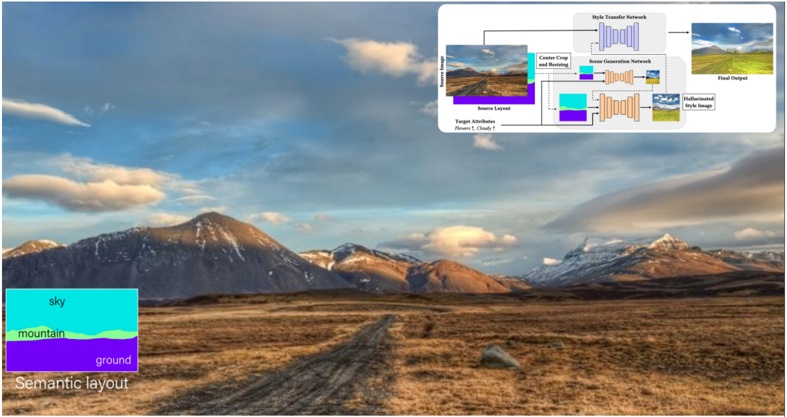
Cycle-Consistent Adversarial Networks



Cycle-Consistent Adversarial Networks



Cycle Consistency Loss

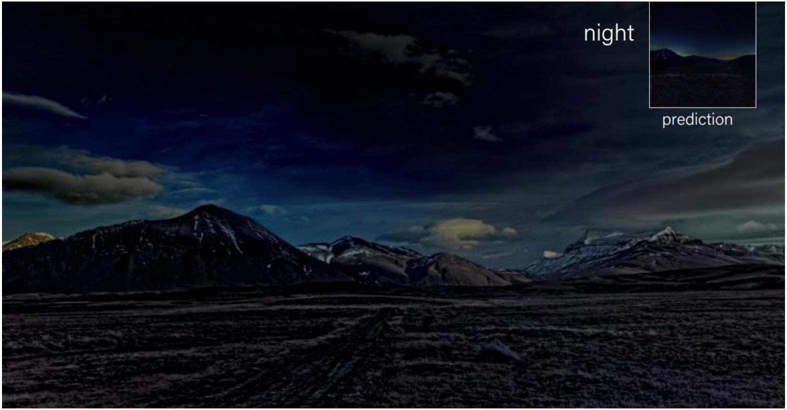


Manipulating Attributes of Natural Scenes via Hallucination [Karacan et al., 2020]

Cycle Consistency Loss

Manipulating Attributes of Natural Scenes via Hallucination [Karacan et al., 2020]

Semantic Image Synthesis (SPADE)



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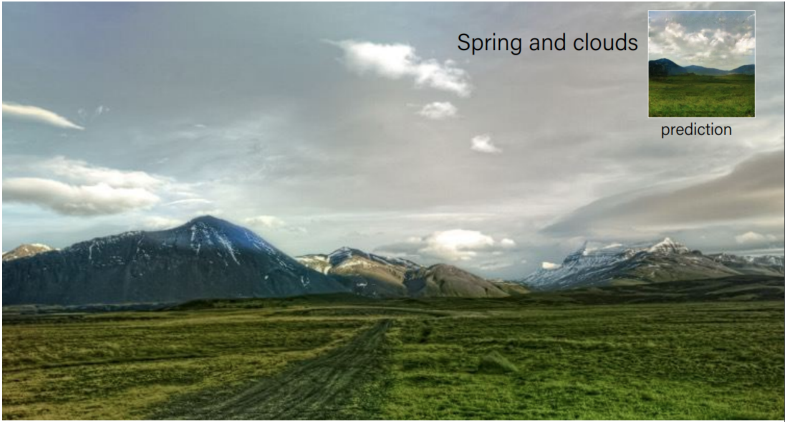

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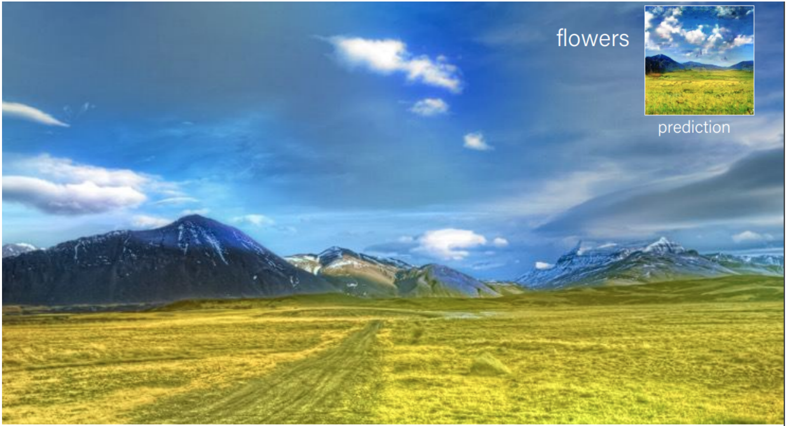

Manipulating Attributes of Natural Scenes via Hallucination [Karacan et al., 2018]